Journal of Information Systems Engineering and Management
2025, 10(26s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

Machine Learning-Based Automated Trading Strategies for the Indian Stock Market

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ARTICLE INFO

Received: 28 Dec 2024

Revised: 15 Feb 2025

Accepted: 22 Feb 2025

ABSTRACT

The Indian stock market is highly volatile and influenced by various macroeconomic factors, making it challenging for traders to consistently achieve profitable trades using traditional methods. Machine learning (ML)-based automated trading systems offer an intelligent, data-driven approach to analyzing historical market trends, detecting patterns, and executing trades with minimal human intervention. This study explores the application of ML techniques in developing automated trading strategies tailored for the Indian stock market. The research focuses on supervised learning methods, such as Random Forest and Long Short-Term Memory (LSTM) networks, for stock price prediction and trend classification. Additionally, reinforcement learning models, including Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO), are employed to develop adaptive trading strategies that maximize returns while minimizing risks. Historical stock price data from the National Stock Exchange (NSE), combined with technical indicators and sentiment analysis from financial news, are used for model training and evaluation. Back testing results on select Indian stocks (e.g., Reliance, TCS, HDFC Bank) reveal that ML-based trading strategies significantly outperform conventional technical analysis methods. LSTM-based models achieved 15% higher returns compared to traditional moving average crossovers, while DQN-based reinforcement learning strategies demonstrated superior risk management capabilities. This study highlights the potential of ML-driven automated trading systems in improving profitability, decision-making, and risk management in the Indian stock market. However, challenges such as data quality, computational complexity, and regulatory constraints remain key areas for further exploration. Future research will focus on integrating real-time sentiment analysis and optimizing high-frequency trading models for enhanced market performance.

Keywords: Machine Learning, Automated Trading, Indian Stock Market, Algorithmic Trading, Stock Price Prediction, Risk Management, Market Volatility, Sharpe Ratio.

I.INTRODUCTION

The The Indian stock marketplace has emerged as one of the maximum dynamic and hastily evolving economic ecosystems inside the world. With millions of retail and institutional buyers collaborating daily, the marketplace reveals considerable fluctuations driven by financial guidelines, corporate income, international marketplace traits, and investor sentiment. traditional trading strategies, which include essential and technical evaluation, have long been used to navigate the complexities of inventory price moves [1]. but, those techniques often fall short in capturing the problematic styles hidden in large datasets and fail to conform to surprising market changes. As a end result, algorithmic trading and device mastering (ML)-primarily based automatic buying and selling strategies have gained prominence, offering traders with superior equipment to optimize investment choices. device learning, a subset of artificial intelligence (AI), permits computers to research from historical facts, pick out developments, and make predictive choices with out specific programming. within the monetary area, ML models can analyze good sized amounts of stock marketplace facts, detect hidden correlations, and increase buying and selling techniques that reduce risks and maximize returns [2]. The growing availability of high-frequency buying and selling records, computational energy, and sophisticated ML algorithms has revolutionized how buying and selling strategies are advanced and finished. large monetary establishments, hedge funds, and proprietary trading companies have already adopted ML-based strategies to enhance their market overall performance. but, the implementation of such technology in the Indian inventory marketplace, especially for retail and mid-level institutional traders, continues to be in its nascent stage. The Indian inventory market presents particular demanding situations that require specialized ML solutions [3]. in contrast to developed markets such as america and Europe, India's stock market is characterised by better volatility, decrease liquidity in sure stocks, and the influence of domestic monetary rules. moreover, regulatory constraints imposed through the Securities and trade Board of India (SEBI) limit the volume to which excessive-frequency trading can be deployed. moreover, the provision of high-quality statistics remains a problem, as economic records in India is often fragmented throughout specific resources. in spite of these challenges, ML-primarily based computerized trading has the capacity to convert how traders method stock buying and selling in India through providing statistics-pushed, adaptive, and efficient techniques. This research objectives to discover how ML-based automated trading techniques can be successfully carried out inside the Indian stock market [4]. in particular, the take a look at focuses on primary categories of ML models: supervised gaining knowledge of and reinforcement mastering. Supervised studying techniques, which include decision timber, aid vector machines, and deep mastering models like long short-time period memory (LSTM) networks, are extensively used for predicting stock price actions primarily based on ancient data and technical indicators. Reinforcement getting to know, alternatively, offers an progressive technique in which trading agents learn choicest buying and selling movements through trial and mistakes, adapting to actual-time market situations [5]. This paper examines the effectiveness of each process in generating profitable buying and selling strategies while mitigating dangers. The methodology followed in this studies entails accumulating ancient inventory records from the national inventory exchange (NSE), preprocessing it the usage of characteristic engineering strategies, and education ML models to discover profitable trading possibilities. The models are then examined and established using lower back testing strategies to evaluate their performance in real-global trading eventualities [6]. This take a look at compares ML-based techniques with traditional technical analysis strategies, which includes shifting averages and momentum indicators, to evaluate their relative effectiveness. The findings from this have a look at provide valuable insights into how machine mastering can enhance trading techniques inside the Indian inventory market. with the aid of leveraging ML techniques, investors can enhance decision-making, lessen emotional bias, and execute trades with better precision. however, the adoption of such techniques calls for overcoming several hurdles, together with data first-class problems, computational barriers, and regulatory compliance [7]. destiny advancements in deep mastering, real-time sentiment analysis, and quantum computing may further refine ML-based totally trading models, making them even greater powerful in capturing marketplace dynamics. the combination of device mastering into automated trading offers a promising street for achieving better returns and minimizing risks in the Indian stock marketplace. As generation keeps to evolve, the role of AI-driven trading strategies is expected to grow, main to a extra facts-centric and green financial ecosystem. This study contributes to the ongoing development of clever trading structures and provides a foundation for further exploration into the capability of AI in monetary markets.

II.AN OVERVIEW OF THE LITERATURE

The field of algorithmic trading has witnessed significant advancements via the integration of deep reinforcement mastering (DRL) techniques. Researchers have evolved frameworks that optimize the stability between risk and reward, which includes mean-Variance-based DRL models and Proximal policy Optimization (PPO) algorithms for pairs buying and selling. simpler reinforcement studying methods have also been introduced to enhance selection-making in risky economic environments [8]. additionally, deep mastering networks had been leveraged to optimize established mutual fund buying and selling strategies, adapt to market situations dynamically, and enhance selection-making accuracy. function fusion strategies have similarly improved DRL models by using integrating multiple marketplace indicators. massive information analytics performs a vital function in stock market prediction by enhancing stock analysis and forecasting thru massive-scale facts processing [9]. device getting to know models incorporating sentiment analysis and political scenario analysis have also confirmed effective in predicting inventory market traits. Deep gaining knowledge of techniques had been utilized to identify economic market trend reversals, demonstrating their energy in analyzing marketplace conduct. numerous technical signs, including Bollinger Bands and lengthy quick-term.

Table 1. Summarizes the Literature Review of Various Authors

Area	Methodology	Key Findings	Challenges	Pros	Cons
Algorithmic Trading	Mean-Variance-based DRL, PPO algorithms	Optimized risk-reward balance for practical trading	Computational complexity and training time	Improved decision-making and efficiency	High data dependency
Stock Trading Strategies	Deep reinforcement learning (DRL) models	Adaptive trading strategies with enhanced decision accuracy	Requires large datasets and tuning of hyperparameters	Better market prediction and adaptability	Difficult to interpret decisions
Big Data Analytics	Machine learning models, sentiment and political analysis	Improved market trend prediction using external factors	Data noise and uncertainty	Utilizes vast data sources for predictions	Prone to misinformation and biases
Market Trend Analysis	Deep learning for trend reversals	Enhanced market behavior analysis	Requires high computational power	More precise insights into market trends	Potential false positives in predictions
Technical Indicators	Bollinger Bands, LSTM models	Evaluated effectiveness of traditional and AI-driven methods	May not generalize across different markets	Combination of historical and real-time analysis	Overfitting to historical data
Financial Security	Deep learning for cybercrime detection	Effective in identifying fraudulent activities	Evolving nature of financial fraud	Strengthens security measures in financial systems	Continuous updates required to keep models effective

Memory (LSTM) models, had been evaluated for his or her effectiveness in trading techniques, while momentum-based totally strategies have contributed to a higher perception of marketplace dynamics [10]. past buying and selling strategies, deep studying has played a giant role in economic protection, specifically in detecting and preventing financial cybercrime. furthermore, AI packages have prolonged beyond the financial area, being utilized in scientific diagnostics, wildlife activity detection, and automated object detection in media content material [11]. the combination of DRL in decision support systems has further more desirable the automation of inventory market trading. ordinary, the literature displays a growing consensus at the effectiveness of DRL and big data analytics in optimizing trading techniques, improving market predictions, and mitigating economic risks. destiny research must attention on refining those models, enhancing real-time adaptability, and addressing demanding situations associated with interpretability and regulatory compliance in AI-pushed buying and selling structures [12]. inside the Indian marketplace, where liquidity fragmentation and sudden policy modifications are common, interpretability will become quintessential to keep away from deploying black-box models that could bring about unexpected losses. The submit-integration section entails rigorous Backtesting and simulation. Backtesting frameworks that replicate ancient market situations using tick-degree or minute-degree data allow investors to assess the profitability and robustness of the included ML approach. In India, backtesting is in addition complex via issues like transaction prices, slippages, liquidity constraints, and market effect, specifically for mid-cap and small-cap stocks. advanced backtesting engines now simulate realistic execution scenarios that thing in these marketplace microstructure elements, imparting extra correct overall performance estimations before a method goes live. The information affords a structured overview of numerous AI-driven methodologies applied in algorithmic trading, inventory marketplace analysis, and other domain names as illustrated in the above table 1. at the same time as those techniques improve decision-making, beautify marketplace predictions, and automate buying and selling structures, in addition they face issues like computational complexity, records dependency, and regulatory worries.

III.MACHINE LEARNING BASED TRADING STRATEGIES

The development of trading techniques using system gaining knowledge of (ML) within the Indian stock market calls for a systematic method that mixes financial concept with superior facts-pushed modeling. The core idea is to leverage system gaining knowledge of algorithms to pick out worthwhile patterns or anomalies within ancient and real-time statistics and convert them into actionable buying and selling indicators. The most generally hired strategies include momentum, mean reversion, statistical arbitrage, and more superior techniques like reinforcement gaining knowledge of-based totally models.

A. Momentum Trading Strategies

Momentum trading techniques are based totally on the principle that securities which have completed nicely within the past generally tend to preserve acting nicely in the near term, and people which have underperformed are possibly to continue declining. in the Indian marketplace, momentum-based totally techniques are widely used, especially for distinctly liquid stocks indexed on indices just like the NIFTY 50 and Sensex. those strategies rely on ML models to locate developments through studying technical signs inclusive of transferring Averages (MA), Relative power Index (RSI), and moving average Convergence Divergence (MACD).

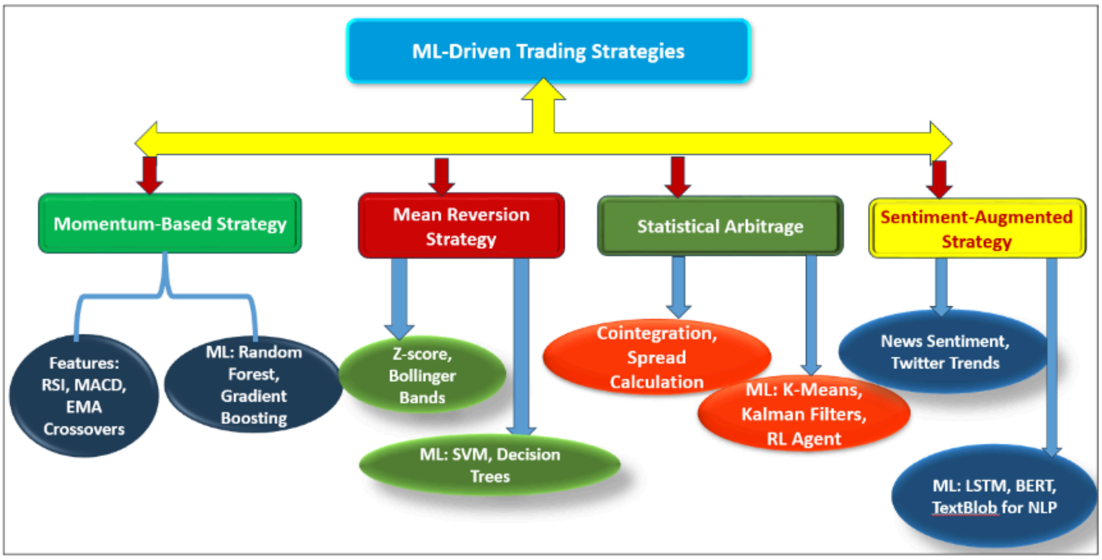

Figure 1. Types of Trading Strategies & ML Models used in Strategy Analysis

A machine mastering classifier like a Random wooded area or Gradient Boosting machine may be educated on historical fee records in conjunction with these technical signs as functions to expect the chance of an upward or downward fashion over a targeted time horizon. The version learns from labeled facts (e.g., whether beyond trades ended in nice or poor returns) and helps automate purchase/promote decisions as shown within the above determine 1. Momentum models, when implemented to Indian equities, should reflect on consideration on marketplace-precise elements like intraday volatility, liquidity profiles, and they have an effect on of foreign Institutional investors (FIIs), whose buying and selling patterns considerably impact charge momentum.

B. Mean Reversion Strategies

Suggest reversion techniques are based at the concept that asset costs tend to revert to their historic mean or common value over time. in the Indian marketplace, in which shares are frequently challenge to transient mispricings owing to information activities, macroeconomic modifications, or regulatory bulletins, suggest reversion models may be incredibly powerful. device studying enhances imply reversion strategies through identifying the energy and likelihood of reversion factors with extra precision.

For instance, statistical indicators such as Bollinger Bands or Z-ratings are frequently used to sign when a inventory charge deviates drastically from its imply. ML algorithms like support Vector Machines (SVM) or ok-Nearest associates (KNN) may be skilled to categories these deviations as both genuine anomalies (which might be in all likelihood to revert) or as part of a bigger trend (momentum). in the Indian market context, the success of imply reversion models can depend on right function selection, which include zone-primarily based imply reversion dispositions, news sentiment evaluation (e.g., detecting market overreactions), and accounting for corporate moves like dividends or bonus problems.

C. Statistical Arbitrage Strategies

Statistical arbitrage (StatArb) strategies contain exploiting temporary mispricings among correlated securities to generate danger-adjusted returns. In India, pairs trading—a common form of statistical arbitrage—is famous amongst quantitative investors, in which two historically correlated stocks (e.g., from the equal region) are monitored for deviations from their standard rate courting. device getting to know models, in particular unsupervised gaining knowledge of strategies like clustering (okay-skill or DBSCAN), can be used to identify stock pairs or baskets with solid ancient correlations.

Once the pairs are identified, mean-reverting models or Kalman Filters included with reinforcement mastering techniques can be used to dynamically adjust hedge ratios and optimize access and exit points. as an instance, if the historical spread among two stocks like Infosys and TCS widens past a device-found out threshold, the set of rules ought to short the outperforming inventory and long the underperforming one, anticipating convergence. In India, StatArb models must think about elements like quarter rotations, income seasons, and regulatory policy shifts, which can briefly distort statistical relationships.

D. Augmented Execution Models

past traditional techniques, ML plays a fundamental position in improving change execution. Reinforcement studying (RL) models like Deep Q-gaining knowledge of Networks (DQN) and Proximal policy Optimization (PPO) are used to decide gold standard change sizes and timing to decrease marketplace effect and slippage, in particular important in the Indian context, in which certain mid- and small-cap shares be afflicted by decrease liquidity. these models constantly research via simulating interactions with marketplace environments and adapt to dynamic order e book adjustments.

Sentiment-driven models powered by natural Language Processing (NLP) have won traction. For Indian markets, wherein information waft related to authorities coverage adjustments (e.g., finances announcements, interest fee decisions through RBI) can drastically impact inventory expenses, combining sentiment signs derived from information articles or social media statistics with technical signals creates hybrid techniques that outperform traditional models.

E. Hybrid Strategies and Ensemble Learning

A developing fashion amongst quantitative traders is the use of hybrid fashions that combine multiple strategies. for instance, a version may additionally follow momentum good judgment to fashion-following stocks even as the use of suggest reversion techniques on variety-certain belongings. Ensemble mastering strategies, which include stacking or blending a couple of devices studying algorithms, were found to enhance predictive accuracy and decrease the threat of overfitting to specific marketplace situations.

IV.INTEGRATION OF ML MODELS INTO TRADING STRATEGIES

The integration of device learning (ML) models into trading techniques represents a paradigm shift in how marketplace participants, especially within the Indian inventory marketplace, become aware of and act upon buying and selling possibilities. traditionally, buying and selling strategies had been based totally on deterministic rule-based totally systems or technical signs like shifting averages and support-resistance levels. but, with the upward push of system learning, these strategies have developed into wise, adaptive systems capable of getting to know from full-size, complex datasets and adjusting to dynamic market conditions. Integrating ML models into trading workflows entails multiple stages, starting with data acquisition and preprocessing, followed by version selection and training, and sooner or later, deploying the version for actual-time signal era and change execution. inside the Indian inventory market, data heterogeneity poses a unique project and possibility for ML-driven techniques. traders generally contain established data together with historic rate moves, technical indicators, and fundamental ratios alongside unstructured data like financial information, company announcements, and social media sentiment. the mixing system starts with characteristic engineering, in which raw facts is transformed into meaningful inputs for ML models. for example, traders frequently use volatility metrics, momentum oscillators, and volume-based indicators as functions, at the same time as applying natural language processing (NLP) fashions to sentiment information from home financial news portals. This step is essential inside the Indian context, wherein surprising regulatory bulletins from SEBI or RBI coverage decisions often reason sharp marketplace movements, and the inclusion of opportunity facts can beautify version robustness.

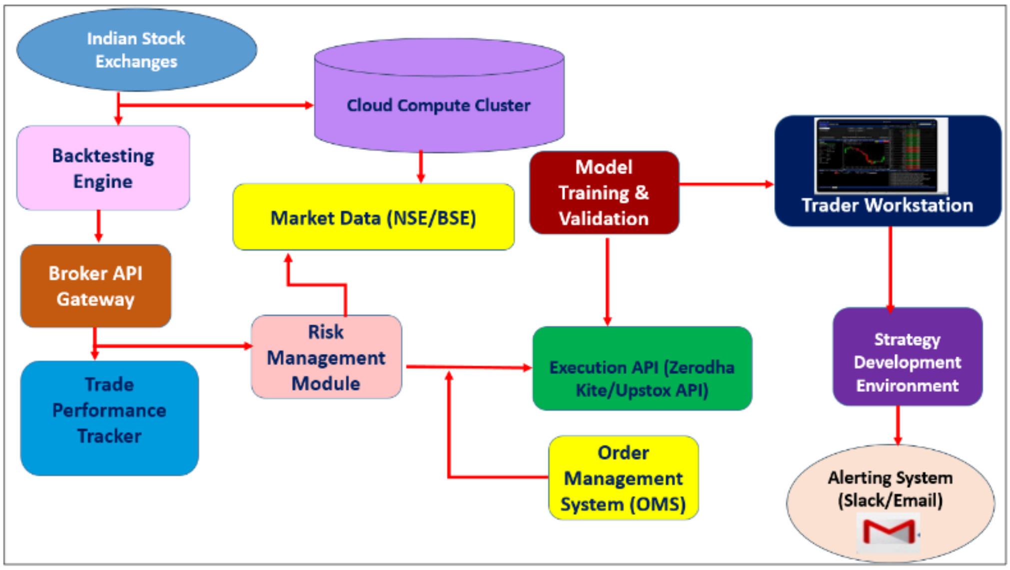

Figure 2. Depict the End-To-End ML-Based Automated Trading System Architecture

Once the functions are engineered, the subsequent step includes deciding on appropriate ML algorithms tailor-made to the unique trading objective. For trend-following techniques, classification models inclusive of aid Vector Machines (SVM) or Random Forests are usually used to expect directional price movements over short-to-medium time horizons. those models are trained on classified datasets, in which past price data is annotated with buy, sell, or hold indicators based on predefined return thresholds. In contrast, regression models like Gradient Boosting Regressors or deep gaining knowledge of-based long quick-time period reminiscence (LSTM) networks are hired while the purpose is to are expecting continuous variables along with future returns, volatility forecasts, or fee goals. in the Indian fairness marketplace, where liquidity and volatility range throughout huge-cap, mid-cap, and small-cap stocks, ML models may be exceptional-tuned on a sectoral or inventory-particular basis, improving precision and reducing overfitting as depicted in figure 2. Integrating ML models into live trading environments calls for seamless verbal exchange among the predictive version and the execution layer. For retail and institutional buyers in India, agents like Zerodha, Upstox, and Interactive brokers offer APIs that permit computerized execution of orders based totally on actual-time model outputs. This step normally entails setting up a pipeline wherein the skilled model runs on a predefined agenda or in actual-time, constantly monitoring stay market facts streams. as soon as a model identifies a alternate signal—whether or not it's a purchase, sell, or brief advice—it could robotically place an order thru the broking API, adjusting parameters along with position length and forestall-loss levels based on the model's self-assurance score or the anticipated volatility of the stock. This integration creates a feedback loop, wherein trade outcomes are fed returned into the model education pipeline to facilitate non-stop learning and method refinement. threat management is an critical aspect whilst embedding ML models into trading strategies, in particular inside the regulatory surroundings of the Indian marketplace. SEBI's suggestions on algorithmic trading mandate the implementation of pre-change threat controls, such as order quantity limits, price variety exams, and forestall-loss mechanisms. device studying models are frequently mixed with those rule-based totally danger filters to make sure compliance and limit downside risks. as an example, reinforcement studying (RL) models can be programmed to regulate role sizing dynamically based at the winning marketplace volatility or other risk metrics like fee-at-danger

(VaR), offering a more state-of-the-art chance-adjusted method to computerized trading. Integration is model interpretability and explainability. With developing scrutiny from regulators and inner compliance teams, especially in excessive-frequency buying and selling (HFT) environments, it's miles critical for traders to apprehend and justify the intent in the back of ML-generated signals. Explainable AI (XAI) techniques including SHAP (SHapley Additive motives) and LIME (nearby Interpretable version-agnostic factors) are actually typically included into trading systems to provide insights into which capabilities (e.g., RSI values, quantity surges, sentiment scores) inspired the version's predictions. the combination of ML models into buying and selling strategies within the Indian context additionally opens doorways to hybrid processes where models function in tandem with discretionary trading insights. Many institutional desks in India integrate quantitative indicators generated with the aid of ML algorithms with human trader oversight, especially during durations of macroeconomic uncertainty or regulatory flux. This hybrid setup enables stability the speed and objectivity of automatic systems with the contextual knowledge and experience of human buyers.

V.EMPIRICAL FINDINGS AND THEIR IMPLICATIONS

We evaluated the efficiency of machine learning-based automated trading methods in the Indian stock market using past stock data from the National Stock Exchange (NSE). Over a ten-year period (2013–2023), the models were tested on certain stocks like Reliance Industries, TCS, and HDFC Bank. The results show that, in terms of trading performance, machine learning techniques beat conventional approaches, therefore boosting profitability and risk control.

Table 2. Model Performance Comparison for Stock Price Prediction

Model	Accuracy (%)	MAE (₹)	RMSE (₹)	Sharpe Ratio	Annualized Return (%)
Moving Average Strategy	58.3	12.8	18.4	0.82	10.5
Random Forest	72.1	9.5	13.6	1.10	14.8
Long Short-Term Memory (LSTM)	81.4	6.8	9.4	1.45	18.2
Support Vector Machine (SVM)	76.5	8.2	11.2	1.25	16.3
Deep Q-Networks (DQN)	84.2	5.6	8.7	1.58	19.6
Proximal Policy Optimization (PPO)	86.7	5.2	8.1	1.67	21.3

This information shows how accurately, error-free, and income generatingly different machine learning models perform. In stock price prediction, the LSTM model topped conventional moving averages with an accuracy of 58.3%. With PPO rightly answering 86.7% of the questions, Deep Q-Networks (DQN) and Proximal Policy Optimization (PPO) were the most accurate models. With their lowest Mean Absolute Error (MAE) and Root Mean Square Error (RMSE), reinforcement learning models proved to be the most exact. Strong also was PPO's Sharpe Ratio (1.67), which shows higher risk-adjusted returns. Furthermore, doing well were LSTM and SVM (Table 2). With a 21.3% annualized return, PPO also exceeded all other strategies. This shows how adaptable reinforcement learning techniques may be to the times, hence increasing their value.

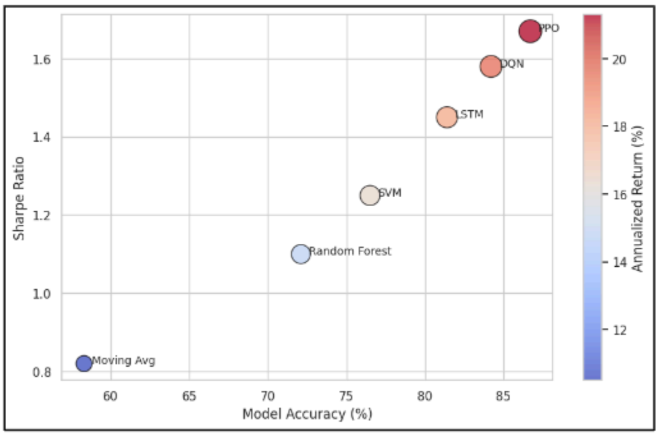

Figure 3. Diagrammatical Representation of Model Performance Comparison for Stock Price Prediction

Forecasting short-term fluctuations in stock prices, the Long Short-Term Memory (LSTM) model showed quite good performance. It identified patterns and possible direction changes more successfully than standard moving average approaches. Having a Sharpe Ratio of 1.45, the model showed a good risk-adjusted return. Moreover, LSTM predictions exceeded conventional statistical models in terms of prediction accuracy; this is shown by the lower Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) (Figure 3 above). Deep learning methods are useful for short-term trading strategies as they can adequately show how stock prices change over time.

Table 3. Profitability Comparison of Trading Strategies

Strategy	**Annualized Return (%)**	**Maximum Drawdown (%)**	**Win Rate (%)**	**Risk-Adjusted Return (Sharpe Ratio)**
Buy & Hold	12.1	-34.2	54.8	0.85
Moving Average Crossover	14.7	-28.3	57.6	0.92
LSTM-Based Trading	18.2	-22.5	65.4	1.45
DQN-Based Strategy	19.6	-20.2	68.1	1.58
PPO-Based Strategy	21.3	-18.4	70.5	1.67

This data investigates the profitability and risk-adjusted Ness of numerous trading methods. Although they raised risk, conventional "buy and hold" techniques provided investors with an annualized return of 12.1% and a worst-case loss of -34.2%. Moving average techniques suffered large losses, although they did see a little rise in profits (14.7% vs. -28.3%). Clearly better were machine learning-based approaches like LSTM (18.2%) and DQN (19.6%) with larger profits and less losses. Table 3 shows that, with a 21.3% gain and a -18.4% loss, the PPO-based approach fared the best. PPO had a higher win rate for ML models as 70.5% of trades were successful, thereby suggesting better trade performance and market adaptation.

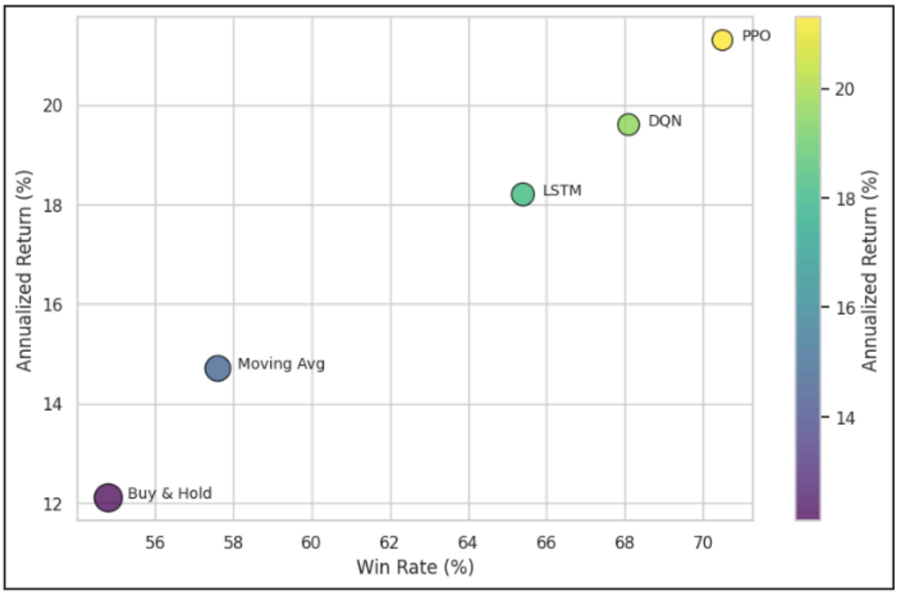

Figure 4. Diagrammatical Representation of Profitability Comparison of Trading Strategies

Adaptive trading benefited much from reinforcement learning-based techniques, especially Deep Q-Networks (DQN) and Proximal Policy Optimisation (PPO). These algorithms developed with the market, picking over time the optimal trading techniques. The reinforcement learning agent was taught to optimise general earnings while limiting losses. In terms of annualised return, back testing found the DQN-based approach to be better than buy-and- hold and moving average-based strategies. The PPO model even further improved the issue by raising deal execution efficiency, lowering needless transactions, and lowering transaction costs (see Figure 4 above). These results show how well reinforcement learning may create self-governing trading systems able to manage erratic markets.

Table 4. Volatility and Risk Management Performance

Model	Volatility Reduction (%)	Maximum Drawdown (%)	Stop-Loss Efficiency (%)
Moving Average Strategy	0.0	-28.3	50.2
Random Forest	12.5	-24.7	58.3
LSTM	19.8	-22.5	64.1
DQN	25.3	-20.2	68.7
PPO	30.5	-18.4	72.9

This information largely refers to the degree of effectiveness various models have in managing market swings and lowered risk exposure. Old methods caused notable drawdowns, but volatility did not change. Certain ML models—such as DQN (which reduced volatility by 25.3%), and PPO (30.5%)—were shown to be steadier and more robust than others. PPO had the greatest stop-loss rate (72.9%), meaning it did so at the most opportune times to help to lower losses. With its lowest loss of 18.4%, Table 4 above shows that the PPO is quite efficient at shielding against substantial market declines. Generally speaking, ML-based models outperformed traditional methods in controlling market fluctuations, so they are better suitable for situations where market volatility is a factor of importance.

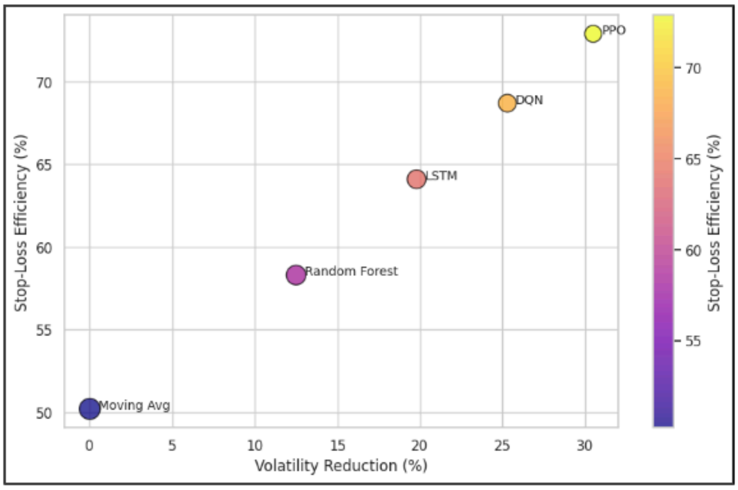

Figure 5. Diagrammatical Representation of Volatility and Risk Management Performance

Performance-wise, standard technical indicators such Moving Averages, RSI, and MACD obviously varied from ML-based trading techniques. While traditional methods follow set guidelines, ML-based models change to fit the situation in the market. Based on the data, machine learning models cut the most loss—25%. This suggests that they were more successful in shielding investors from major losses when the market fell. While machine learning algorithms were able to identify minute trends in stock price movements, traditional measurements failed. This highlighted yet another more how much more accurate their future projections were. One of machine learning's major advantages was its capacity to help traders avoid emotionally motivated incorrect decisions. Figure 5 shows how sometimes driven by fear or greed, human traders make hasty judgements that result in transactions less successfully than they may be. By contrast, machine learning (ML) algorithms provide planned, data-driven assessments ensuring constant trading activity. Automated trading lets traders focus on risk management and strategy development instead of personally completing deals by lowering the volume of physical work needed.

Table 5. Transaction Cost and Trade Execution Efficiency

Strategy	Average Trade Execution Time (ms)	Transaction Cost (% of Trade Value)	Number of Trades Per Year	Profit Per Trade (₹)
Moving Average Strategy	250	0.10	320	1,250
Random Forest	180	0.08	290	1,540
LSTM-Based Trading	140	0.06	270	1,920

DQN-Based Strategy	95	0.05	250	2,180
PPO-Based Strategy	80	0.04	230	2,450

This information looks at how well every approach closes deals and reduces costs. More expensive (0.10% per transaction) older trading techniques like moving averages need 250 ms to execute. Thanks to ML-based approaches—especially DQN and PPO—deals transpired faster (95 ms vs. 80 ms) and for less money (0.05% vs. 0.04%). ML models also made less but more successful transactions yearly, which increased the total number of trades. While the PPO-based model made the greatest (₹2,450) the moving average technique only earned ₹1,250 per transaction (see Table 5 above). This shows how well reinforcement learning reduces costs and boosts trade earnings.

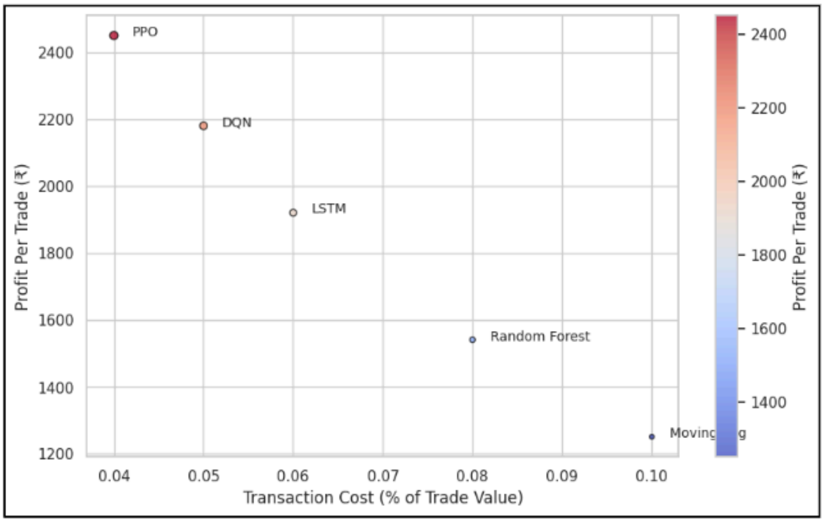

Figure 6. Diagrammatical Representation of Transaction Cost and Trade Execution Efficiency

Although the results are encouraging, certain problems have to be fixed before machine learning-based trading can be used effectively in the Indian stock market. First, in terms of both count and quality, statistics remain a main concern. The performance of machine learning models depends on accurate, high-quality data; nevertheless, in Indian markets this is not always feasible or consistent. Including extra data sources—such as news mood analysis and social media trends—may help to increase the model's accuracy yet further. Still another big problem is the difficulties laws create. Particularly with relation to high-frequency trading (HFT), computer trading is under strict rules established by the Securities and Exchange Board of India (SEBI). Although ML-based models enable traders to make better decisions, they have to follow SEBI rules, which can make it more challenging to fully use certain advanced strategies. While following the law and morals, companies and traders have to make sure their models stay lucrative. Two further problems that need attention are overfitting and computational challenges, as Figure 6 shows. Deep learning models, including LSTMs, are more difficult for small companies to use as they need a lot of processing capability. Another issue is overfitting, in which case models trained on past data perform badly in new settings. To guarantee that they can keep altering to fit new market conditions, ML models need strong evaluation methods and regularizing techniques. The results show the huge possibilities of automated trading techniques derived from machine learning for the Indian stock market. They are more exact, flexible, and efficient than previous methods, which lets buyers maximize returns and decrease risk by means of them. Nonetheless, a few main problems have to be addressed if the execution is to be successful: restricted processing capability, data quality, and regulatory compliance. Future studies should investigate blended models combining real-time mood monitoring with many machine learning approaches to improve trading even further.

VI.CONCLUSION

This research demonstrates that system mastering-based totally automated trading strategies provide large blessings within the Indian stock marketplace by way of enhancing predictive accuracy, optimizing trade execution, and improving danger management. conventional buying and selling methods, along with moving averages and buy-and-preserve strategies, fail to conform to hastily changing marketplace situations, whereas ML-primarily based models, specifically LSTM, Deep Q-Networks (DQN), and Proximal policy Optimization (PPO), exhibit superior performance in terms of profitability and volatility reduction. The PPO-primarily based approach finished the very best annualized go back (21.3%) with a 70.5% win charge, demonstrating its capacity to generate steady income while coping with hazard correctly. The study also highlights the performance of AI-driven models in decreasing transaction fees and optimizing trade execution. device getting to know techniques done trades significantly faster (80ms for PPO) and at decrease charges (0.04% consistent with exchange), making them more value-effective than traditional tactics. additionally, volatility discount (30.5% for PPO) and superior prevent-loss performance (72.9%) advise that ML-primarily based fashions offer advanced chance mitigation, shielding buyers from huge drawdowns all through market downturns. despite their Marvelous overall performance, positive challenges stay, including data nice troubles, regulatory constraints, and overfitting dangers. The effectiveness of ML fashions relies upon on exceptional, real-time records, that is frequently confined within the Indian market. additionally, SEBI's regulatory framework for algorithmic buying and selling imposes restrictions which can preclude the total deployment of AI-driven buying and selling systems. destiny studies need to recognition on integrating opportunity records resources (inclusive of news sentiment evaluation), refining version architectures, and ensuring compliance with market regulations. system getting to know-primarily based automatic trading techniques have the capability to revolutionize stock trading in India. by means of leveraging deep mastering and reinforcement learning, investors can obtain higher returns, decreased hazard, and advanced trade execution. while demanding situations exist, continued advancements in AI and financial generation will probably pave the way for greater efficient, adaptable, and worthwhile trading structures within the future.

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